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# Dynamic optimization models for displaying outdoor advertisement at the right time and place

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Abstract: Digital billboards, as a new form of outdoor advertising, has gained popularity in recent years per its revolutionized way to control when and where the specific ads appear. However, this development also demands more complicated optimization for strategic deployments: the advertisers have to not only decide on a set of locations to display their ads, but also when to display them. The existing static optimization approaches become insufficient for this dynamic scenario to match advertisement and intended audience. Therefore, this research proposes three models in a workflow to mine mobile phone data and points of interest (POIs) data and to meet advertising needs in various situations. The three optimization models include a dynamic audience model to maximize the coverage of the target users, a dynamic environment model to maximize the coverage of the target environment, and a dynamic integrated model to maximize the coverage of both target audience and environment. A case study using shopping ads in Wuxue, China tests the three optimalization models. The results show that the proposed models are effective for providing an optimal solution for digital billboard configuration with a greater coverage of the target audience and environment compared to the state-of-the-art static models.

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# Dynamic optimization models for displaying outdoor advertisement at the right time and place

**Abstract**: Digital outdoor advertising, as a new form of outdoor advertising, has grown significantly in recent years. It has revolutionized the way to display ads by allowing to control when and where the ads are shown. However, this development also leads to more complicated optimization of the deployments: the advertisers have to not only decide on a set of locations to display their ads, but also when to display them. The existing static optimization approaches become insufficient for this dynamic scenario. Therefore, this work attempts to bridge this gap by mining mobile phone data, and points of interest (POIs) data. Considering the real advertising needs in various situations, three optimization models are proposed: a dynamic audience model to maximize the coverage of the target users, a dynamic environment model to maximize the coverage of the target environment, and a dynamic integrated model to maximize the coverage of both target audience and environment. The proposed models were applied in Wuxue, China, by using shopping ads as an example. The results show that the proposed models are effective for providing an optimal digital billboard configuration solution, and achieve a higher coverage of the target audience and environment compared to the state-of-the-art static models.
**Keywords:** digital outdoor advertising; mobile phone data; maximal coverage location problem

## 1. Introduction

Out-of-home (OOH) advertising or outdoor advertising is a highly effective way to reach potential consumers outside of their homes. The most common and traditional form of outdoor advertising is static billboards, but there has been significant growth in digital outdoor advertising in recent years. According to PricewaterhouseCoopers (PwC), digital outdoor advertising has increased by 35 percent since 2010, and it is projected to overtake traditional ad spending by 2020 (PwC Global 2019, Schulz 2019). The pervasiveness of digital billboards is partially due to their flexibility in contents display and ad deployment. Advertisers are no longer charged by an extended period, for example, months or years, instead, they can rent the digital billboards at specific periods and locations to display their ads according to where their target audience is located. However, the new convenient and economical solution leads to more complicated optimization of the deployment of the ads. In addition to decide on a set of locations to display the ads, now advertisers also have to decide when to display them.

Not only the new form but also the new location data (e.g., GPS data and mobile phone data) is revolutionizing outdoor advertising. Over one hundred years ago, John Wanamaker, a pioneer in marketing, proclaimed, “Half the money I spend on advertising is wasted; the trouble is, I don’t know which half” (Ogilvy and Horgan 1963). Conventional outdoor advertising has mainly depended on geodemographic data, traffic volume, etc., which often lead to undesirable ad placements and coarse-grained performance estimation (Zhang *et al.* 2018). Nowadays, a richer array of location data sources is available, e.g., GPS data, mobile phone data, and social media data. They potentially allow advertisers to have a much better understanding of who are passing by, where they are going, and what makes them tick (Kantor 2018). With the advent of these new data sources and the new form of outdoor advertising, now we get the opportunities to identify and save the “wasted” money by displaying outdoor advertisement at the right time and place. However, the related research is still at an infant stage. Few studies have focused on using these new datasets for targeted outdoor advertising. More importantly, these existing studies often fail to consider the dynamic and multi-criteria nature of digital outdoor advertising (Quercia *et al.* 2011, Lai *et al.* 2017, Anagnostopoulos *et al.* 2018, Huang *et al.* 2019). For example, after identifying target audience, these existing studies often take the target users’ most frequent location as the place for advertisement, without considering that the audience might continually move over the day. There are also studies trying to ensure the harmonization of the ads’ content with the surrounding environment (Zhang *et al.* 2017, Hua 2019). However, they mostly assumed that the location carries a temporally constant semantic meaning, and ignored the temporal dynamics of the environment (e.g., fluctuating demand due to the service hours of the nearby points of interest, POIs). In summary, existing studies on outdoor advertising fail to consider the spatio-temporal movement of the target users and the temporal dynamics of the environment. This often leads to undesirable ad placements, which underutilizes the potential of digital outdoor advertising and thus significantly reduces the effectiveness of advertising campaigns.

To address this gap, this study proposes three location optimization models to improve the coverage of the target audience and environment for outdoor advertising. Specifically, we use mobile phone data to identify the target users and analyze their spatio-temporal movement pattern. Based on the data and analysis, a *dynamic audience model* is proposed to maximize the coverage of the target audience. Besides, we utilize POI data (and their service hours) to represent the temporal dynamics of the environment. A *dynamic environment model* is then proposed to maximize the coverage of the target environment. Finally, an *integrated model* is proposed to jointly account for the dynamic features of both the target audience and the environment. Hence, taking shopping ads as an example, we are able to estimate the most promising time slots and places to display them according to different advertising needs. If other categories of ads are of interest, the proposed workflow and methods can also be applied.

The main contributions of this study are summarized as follows.

1) From a methodological perspective, this work extended the existing continuous space maximal coverage methods, which mostly assume static demands of locations, with time-varying location demands. This extension allows to deal with demands that vary at spatio-temporal dimensions (e.g., in this study, the target users might find themselves at different locations at different time periods). While this work focused on digital outdoor advertisement, the proposed method can also be used for other facility siting scenarios when demands are continuously distributed and time-varying.
2) From an application perspective, we propose a target-oriented framework for the deployment of digital billboards with the integration of mobile phone data and POI data into three location optimization models. To the best of our knowledge, this is the first work attempting to improve the digital outdoor advertising effectiveness considering the spatio-temporal movement of the target users, and the temporal dynamics of the environment. The proposed models were applied to a real mobile phone dataset and POI dataset to demonstrate their feasibility and effectiveness in targeted digital outdoor advertising. The evaluation shows that the proposed models achieve higher coverage of the target audience and the target environment, compared to the state-of-the-art static methods.

## 2. Related work

### *2.1. Factors influencing the effectiveness of digital billboard advertising*

*a) Audience matching*

The deployment of billboards is a multi-criteria decision making (MCDM) problem (Liu *et al.* 2017). To launch a successful advertising campaign, advertisers usually have to consider multiple criteria. One of the most considered criteria is audience targeting, which means to maximize the ads' exposure to the users who may be interested in the ads (Anagnostopoulos *et al.* 2018, Jiang *et al.* 2018, Huang *et al.* 2019). The more relevant the ad is to the user, the more attractive the ad might be (Malheiros *et al.* 2012). The targeted advertising aims to match the ads with the users' interests, which has been proven effective to capture users' attention and deliver ad information (Tam and Ho 2006, Tucker 2014).

Even though targeted digital outdoor advertising is still at an early stage of development compared with online advertising, a growing number of studies have been making contributions to it in recent years. Lai et al. (2017) detected topical themes from Twitter data, which were then used for targeted advertising in the London Underground network. Anagnostopoulos et al. (2018) leveraged social media data for interest-driven outdoor adverting. Huang *et al.* (2019) inferred users' interests from app usage and used them to empower targeted advertising. However, existing studies have mainly focused on the static scenario of targeted advertising, which means the advertising places are fixed during the whole period. Hence, when applying target users' traces for advertising placement, the spatio-temporal dynamics of audience movement is often ignored, and instead the average daily flow or daily circulation in an area is often used to represent the target users (Quercia *et al.* 2011, Lai *et al.* 2017, Anagnostopoulos *et al.* 2018, Huang *et al.* 2019). Limited efforts and attention are paid to the dynamic scenario of digital outdoor advertising. As a result, there is an urgent need to develop methods that can incorporate the spatio-temporal dynamics of audience mobility, namely, where the target users visit at different time, to help advertisers decide when and where to display their ads.

*b) Environment matching*

In addition to the match between the audience and the contents of the ads, the matching between the surrounding environment and the ads is also a criterion that should be considered (Zhang *et al.* 2017, Hua 2019). The harmonization of the ads with their surrounding environment can help to improve the effectiveness of the ads, namely, increasing user's attention and purchase intent to the ads (Wilson and Till 2011). On the contrary, the discrepancy between them may deliver inappropriate ads content and even lead to cognitive confusion (Hua 2019).

Environment context includes many factors, e.g., the geographical environment, the weather conditions, the social surroundings, etc. (Huang 2016, Molitor *et al.* 2016). Here, we mainly refer to the geographical environment, specifically, the POIs combination in the area. POIs are often used to enrich the semantics and significance of places (Krüger *et al.* 2014, Cheng and Shen 2018). They can be regarded as indicators associated with specific urban functions, such as shopping, education, or business. Several studies have adopted regional POIs to analyze the relationship between the locations and the contents of the ads. Zhang *et al.* (2017) used bus stations' surrounding POIs to characterize the bus stations for transit advertising. Wang *et al.* (2019) analyzed the categorical distribution of users' destination POIs, which was further utilized to evaluate the matching degree with advertising contents. However, almost all of these studies assumed that the location carries a temporally constant semantic meaning, and ignored the temporal dynamics to which the environment is often subjected. In fact, some environmental contexts can vary over time in a complex manner and different types of POI may have different temporal visiting signatures (McKenzie, Janowicz, Gao, Yang, *et al.* 2015, Wang and Kwan 2018). For example, in the case of shopping areas, the environment changes with the opening and closing of the shopping malls and stores, so the same place might be labeled as residence area and shopping area at different times of the day. Similarly, many stores also have a different opening schedule for weekdays and weekends. Hence, even for the same place at the same time, its effectiveness for outdoor advertising might change over weekdays and weekends.

As discussed above, audience matching and the environment matching are both critical to the success of outdoor advertising. They have been studied separately in the literature, but few studies have examined them jointly in an integrated manner. More importantly, previous studies ignored the spatio-temporal dynamics of both the audience mobility and the environment, which are of great importance to launch a successful digital billboard advertising campaign.

### *2.2. Digital billboard location selection models*

*a) Maximal coverage modelling: discrete point-based demands vs. continuous space-based demands*

Considering the audience and the environment matching, our goal is to find a set of locations to display the shopping ads that would maximize the exposure to the total number of users who are interested in shopping or maximize their agreement with the target environment over the whole time horizon, which is 24 hours from 00:00 to 24:00 in this study. To simplify the problem, a budget limit is not considered. From the perspective of location theory, this placement problem can be solved based on the maximal covering location problem (MCLP), proposed by Church and ReVelle (1974) (Detailed information about MCLP can be found in the Appendix). The digital billboards can be seen as facilities, providing ad contents as a service to the people and environment around them. The target audience and target environment can be seen as demands that need to be covered. Each billboard's influence range is represented by a circle of a certain radius. Once the demands have been placed within the influence range, they are declared as covered.

In the MCLP, both the demand and the potential facility sites were considered as a finite set of discrete points. In our case, the POIs can be regarded as point-based demands. Once they are inside the influence range of billboards, they are regarded as covered (Fig. 1a). However, this finite and discrete assumption in the MCLP may not be appropriate in some cases, such as the target users in this study, who are continuously distributed over the study area. Therefore, it is not suitable to represent them as points, e.g., the locations of mobile phone towers: when a mobile phone tower is within the influence range of a billboard, it does not mean that the entire users served by this tower are indeed covered. This is mainly due to the fact that the service area of the mobile phone tower is often very large, and can be even up to several square kilometers (Huang, Cheng, *et al.* 2019). This kind of location problems is often formulated as a continuous space maximal coverage problem.

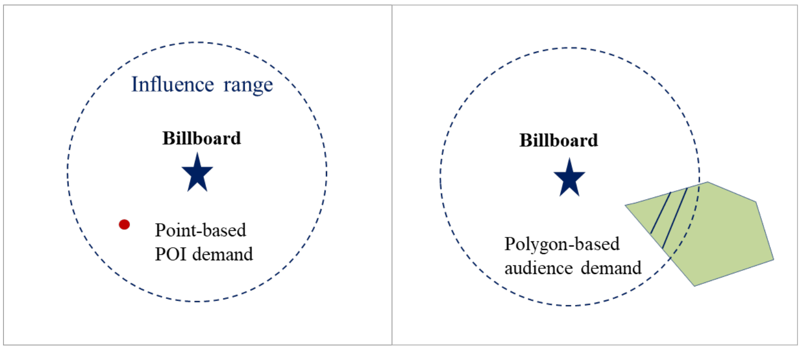


Figure 1 (a) point-based coverage, adopted in the classic MCLP; In this case, both the demands and the potential facilities (i.e., billboards in this work) are modelled as a finite set of discrete points; (b) polygon-based coverage, adopted in continuous space version of the classic MCLP; the demands are continuously distributed over a region, and therefore modelled as a polygon.

In the continuous space version of the MCLP, the demand is continuously distributed over a region, so the demand for a facility can arise almost anywhere rather than at discrete point locations (Church and Murray 2018). Since the simplification of point representations can induce significant errors and bias, more realistic spatial objects, e.g., lines or polygons, are increasingly applied to represent continuous demand (Wei 2016). However, when the demands are represented as non-point spatial objects, the MCLP cannot be applied anymore, since a line or polygon object could be partially covered, which violates the binary coverage assumption in the MCLP (Fig. 1b). As a result, a few new maximal coverage models, for example, MCLP-explicit (Tong and Murray 2009), MCLP-implicit (Alexandris and Giannikos 2010, Murray *et al.* 2010), and MCLP-complementary coverage (MCLP-CC) (Tong 2012) have been developed to deal with polygon-based demand representation. Among these models, the MCLP-CC is regarded as the most promising one in terms of computational efficiency and coverage efficiency (Wei 2016) (Detailed information about MCLP-CC can be found in the Appendix).

*b) Maximal coverage modelling with time-varying demands*

Another issue that should be addressed is that in the context of digital billboard advertising, multiple time periods are involved, which leads to a dynamic planning problem (Canel *et al.* 2001). For example, when considering audience matching, the target audience (i.e., the demands) might be located at different places at different time periods, which leads to time-varying demands. To address this issue, the above described models (either point-based MCLP or their continuous space versions (e.g., MCLP-CC)), which were developed for static demands, should be extended.

Several studies have focused on extending the point-based MCLP to its dynamic counterparts (Boloori Arabani and Farahani 2012). For example, Schilling (1980) proposed a first dynamic maximal covering location problem (DMCLP) for public-sector facilities. More recently, Zarandi *et al.* (2013) studied the large-scale dynamic MCLP using a simulated annealing (SA) approach. Tu *et al.* (2016) proposed a novel spatio–temporal demand coverage location model for the optimal location of electric taxi charging stations.

However, extending continuous space-based MCLP with time-varying demands has by far been overlooked in the literature, even though this extension can lead to more suitable results (Seyedhosseini *et al.* 2016). In this study, we will extend the MCLP-CC to the dynamic version, with the aim of providing an optimal digital billboard deployment solution over spatio-temporal dimensions.

## 3. Methodology

### 3.1. *Overview of the methodology*

The framework of this study is shown in Figure 2. Two kinds of data, mobile phone data and POI data are used to identify the target audience and target environment, as introduced in (Section 3.2). In the static scenario, the MCLP-CC model is applied to maximize the coverage of the target users and the MCLP model is applied to maximize the coverage of the target POIs, which are used as baselines to compare with our proposed models, but neither the spatio-temporal movement of the target users nor the temporal dynamics of the environment is considered in the static scenario. We further take these dynamic factors into account to develop the dynamic scenario in Sections 3.3 to 3.5: considering the spatio-temporal movement of the target users, a dynamic audience model is proposed to maximize the coverage of the target users (Section 3.3); considering the temporal dynamics of the environment, a dynamic environment model is proposed (Section 3.4), and a dynamic integrated model is proposed to maximize the coverage of both target users and environment (Section 3.5).

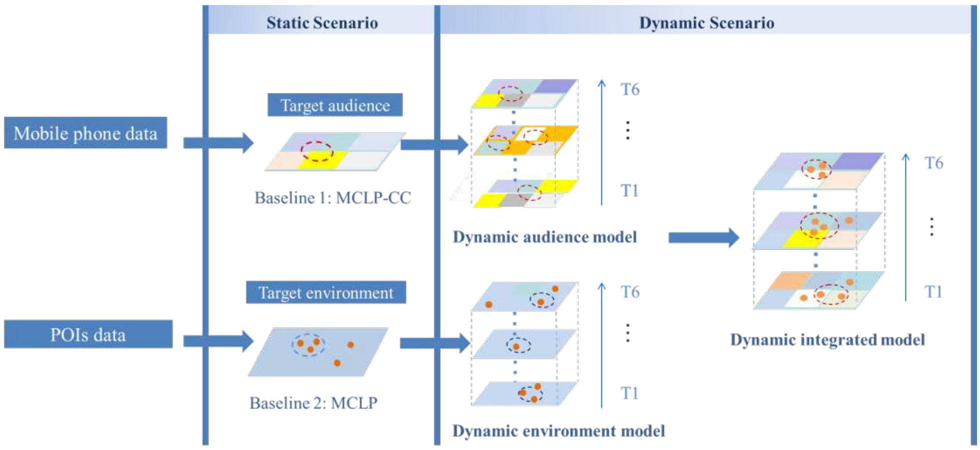


Figure 2 Framework of the digital billboard siting method

### 3.2. *Data Introduction*

Two kinds of data are used in this study. A basic introduction of the datasets is given below.

**Mobile phone data:** There are two kinds of mobile phone data used in this study, namely mobile internet usage data and mobile phone location data. All the data is anonymous without any personally identifiable information. Please note that, due to the high potential of generating revenues from these data, many mobile network operators, e.g., Vodafone, AT&T, have recently started to explore the multiple usages of their data (Ember 2016, Huang, Cheng, *et al.* 2019, Paulina 2019). In other words, these kinds of mobile phone data can be expected to become more and more available.

a) The mobile internet usage records are recorded every time the user makes internet access requests. The corresponding records include an anonymous user ID, a timestamp, the website or app visited, ID of the cell phone tower the phone connects to, and the amount of consumed data. Table 1 provides some examples of these data. In this study, mobile internet usage data are used to estimate a user's interest and thus identify the target audience.

b) The mobile phone location records are automatically recorded by the mobile network operators in the following scenarios: (1) when a user has a mobile phone activity, e.g., a call, a message or an internet access; (2) when a user moves to an area served by another mobile phone tower; (3) if a user does not have any mobile phone activity for serval hours, his/her location would be actively updated (Huang, Cheng, *et al.* 2019). Typically, each record contains the following fields: an anonymous user ID, a timestamp, the ID of the cell phone tower that the phone is connecting to, and longitude and latitude of the corresponding cell phone tower. Table 2 shows some examples of these data. In this study, mobile phone location data are used to model the spatio-temporal movement of the target users.

Table 1 Sample records of mobile internet usage data

| User ID | Date | Time | Base | App | Data |
|---|---|---|---|---|---|
| 36038 | 2015-08-10 | 08:34 | 133 | WeChat | 0.0107 |
| 36038 | 2015-08-10 | 09:43 | 150 | WeChat | 0.0017 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 36038 | 2015-08-10 | 11:30 | 333 | Taobao | 1.32 |

Table 2 Sample records of mobile phone location data (the position is marked for privacy)

| User ID | Date | Time | Base | Longitude | Latitude |
|---|---|---|---|---|---|
| 58443 | 2015-08-10 | 07:32 | 111 | 115.**** | 29.**** |
| 58443 | 2015-08-10 | 08:32 | 111 | 115.**** | 29.**** |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 58443 | 2015-08-10 | 09:27 | 125 | 115.**** | 29.**** |

**POI data:** POI data refer to the geographical entities that can be represented as points. They are usually available in most web mapping service platforms, such as Google Maps and Baidu Maps. A POI often includes the following information: name, category, longitude and latitude, and service hours (if applicable). Typical categories of POIs are residential buildings, schools, restaurants, etc. This study mainly uses POI data and their service hours to model the temporal dynamics of the environment.

### *3.3. Audience matching*

To achieve the targeted outdoor advertising, the first step is to identify the target audience, that is, in this study people who are interested in shopping. Using mobile apps is now becoming a common activity in daily life, resulting in large amounts of mobile internet usage data. Mobile internet usage data can reflect user interests and has thus been applied to construct user interest profiles for recommendation and online targeted advertising (Boerman *et al.* 2017). In this study, we utilize it to identify people who are interested in shopping for outdoor advertising. Since different apps and websites in the same category play similar roles in reflecting the preference of users, we aggregate them into 12 different categories according to their function. This categorization process is done manually according to the detail introduction of the apps on the app download webpage. The categories and the corresponding number of apps are shown in Table 3.

Table 3 The 12 functional app categories used in this study

| Category | Number of apps | Category | Number of apps |
|---|---|---|---|
| Music | 20 | Reading | 27 |
| Social networking | 20 | Game | 28 |
| Business | 24 | Online shopping | 28 |
| Instant message | 24 | Maps and travel | 29 |
| News | 24 | Finance | 36 |
| Life | 27 | Video | 41 |

Each user's interest profile is represented in the form below:

$$\{(c_1, s_{m1}), (c_n, s_{mn}), \ldots (c_{12}, s_{m12})\} \tag{1}$$

where $c_n$ stands for the interest category $n$, corresponding to a category in Table 3. $s_{mn}$ is the weight of user $m$ of interest category $n$, representing user $m$'s degree of interest in category $n$. A simple way to define $s_{mn}$ is to assign it based on the amount of data user $m$ utilized for category $n$, which can be formulated as:

$$p_{mn} = \frac{d_{mn}}{\sum_{n} d_{mn}} \tag{2}$$

where $d_{mn}$ represents the data of category $n$ consumed by user $m$ and $\sum_{n} d_{mn}$ is the data of all categories consumed by user $m$. However, this method may lead to biased results because most people more frequently use social networking and instant message apps. As a result, the majority of people would be identified as interested in social networking, which is far from reality (Huang *et al.* 2019). Hence, directly using the data usage to identify users' interests is not appropriate.

To address this issue, a baseline, reflecting whether a given category is generally popular or rarely used among all the users, is applied to normalize the contribution of the data-heavy app categories. Specifically, for interest category $n$, the data usage ratio $B_n$ of the total users is calculated as a baseline as follows:

$$B_n = \frac{\sum_{m} d_{mn}}{\sum_{m}\sum_{n} d_{mn}} \tag{3}$$

where $\sum_{m} d_{mn}$ represents the data consumption of category $n$ by all the users, and $\sum_{m}\sum_{n} d_{mn}$ is the total consumed data by all the users. Then, for each user, the data consumption ratio of a specific category is compared with the corresponding baseline to acquire $s_{mn}$ as follows:

$$s_{mn} = \frac{p_{mn}}{B_n} \tag{4}$$

With this, the effects of the data-heavy app categories are eliminated. A high weight larger than one indicates that the user consumes the corresponding category of apps above the average level. The dominant interest of one user is identified as the category with the highest weight. In this study, the group of people who are dominantly interested in online shopping is selected as our target audience.

After identifying the target users, their trajectories are utilized to estimate the size of the target audience in different areas during each time period. In this study, mobile phone location data is applied to acquire the dynamic mobility of the target audience. The pervasive use of mobile phones enables us to estimate much more fine-grained dynamic audience population data compared with traditional census data, and it provides an opportunity to capture the spatio-temporal movement of the target audience.

As mentioned in Section 2.2, since the target audience is continuously distributed over the study area, it is more appropriate to represent them by polygons rather than points. Therefore, in this study, the Voronoi polygons generated by mobile phone towers are used to denote the corresponding target audience. The Voronoi polygons are a commonly used subdivision when dealing with mobile phone data, and this division is an effective way to approximate daytime population, but less precise in areas with low mobile phone tower density (Deville *et al.* 2014, Xu *et al.* 2015, De Meersman *et al.* 2016). In this study, since we only selected a study area having a high mobile phone tower density, we think the bias caused by this subdivision should be small and will not have a big effect on model results. For each Voronoi polygon, distinct target audience counts are generated during each time period according to the mobile phone records of target users, and they are assumed to be uniformly distributed within the Voronoi polygon. Demand objects are often weighted based on the associated information to reflect their significance. In this case, during each time period, the number of target users that pass by is then used as the weight of each Voronoi polygon.

Before the new dynamic model is introduced, consider the following notations:

$i$ = index of polygon demand (i.e., target audience) where $i=1,2,...I$

$k$ = index of the potential facility (i.e., billboard) locations where $k = 1,2,...K$

$p$ = number of facilities (i.e., billboards) to be located

$t$ = index of time periods where $t = 1,2,...T$

$w_{it}$ = weight of Voronoi polygon $i$ during time period $t$, determined by target audience population during $t$

$\alpha_{it}$ = the total covered target audience in polygon $i$ during time period $t$

$\Omega_i$ = set of facilities (i.e., billboards) that can provide some coverage to demand polygon $i$ (i.e., target audience in polygon $i$)

$b_{ikt}$ = the number of target users in polygon $i$ covered by billboard located at $k$ during $t$

$$x_{kt} = \begin{cases} 1, & \text{if a billboard is located at } k \text{ during the time period } t \\ 0, & \text{otherwise} \end{cases}$$

By extending the MCLP-CC to the multi-period case, we can obtain the dynamic solution of this problem, which we term the dynamic audience model. The whole time horizon is divided into $T$ periods, and the formulation is then as follows:

$$Maximize \ \ f_1 = \sum_t^T \sum_i^I \alpha_{it} \tag{5}$$

$$subject\ to{:}\ \alpha_{it} \le \sum_{k \in \Omega_i} b_{ikt} x_{kt},\ \forall i,\ \forall t \tag{6}$$

$$\alpha_{it} \le w_{it},\ \forall i,\ \forall t \tag{7}$$

$$\sum_t^T \sum_k^K x_{kt} = p \tag{8}$$

$$x_{kt} \in \{0, 1\},\ \forall k,\ \forall t \tag{9}$$

The objective equation (5) seeks to maximize the number of target users over the whole time horizon, which is one day in this study. The constraint equation (8) specifies that the total number ($p$) of the billboards can be adopted over the whole time horizon, but the optimal number during each period is to be found by solving the model. The constraints (6) combine all the coverage to target audiences by summing up all coverage provided by each located billboard during a single time period. Constraint (7) specifies the upper limit of the total coverage that each area can receive during a single time period. The constraint (9) imposes the integer requirements on site selection variables.

In general, there are two strategies to solve the above location optimization problem: exact methods and heuristic methods. Exact methods are those generating a provably optimal solution. Common exact methods include enumeration, branch-and-bound, linear programming, and integer programming (Tong *et al.* 2009). However, when the problem size grows, the computational effort often increases dramatically. Heuristic methods are preferred for solving such problems due to the NP-hard structure of the given optimization problem. Heuristic approaches, including tabu search, genetic algorithms (GAs), simulated annealing, and others, can often solve a problem faster but the solution quality cannot be guaranteed (Fang *et al.* 2013, Tu *et al.* 2014, Tong and Murray 2017)

### 3.4. Environment matching

As mentioned in Section 2.1, by environment matching, we refer to how well the contents of the ads match the POIs in the area. The target POIs are the POIs category that matches the category of the ads to be displayed. POIs are typically organized by a hierarchical category tree (Liu *et al.* 2013). In each main category, the locations are then classified into different subcategories, e.g., shops as the main category consist of grocery stores, electronic stores, etc., as subcategories. In this study, the category refers to the main category of POIs. Mismatches at lower levels are not considered. Hence, for shopping ads, if an area has a high density of stores and shopping malls, this area will be regarded as a well-matched place for shopping ads. The temporal variation of the environment is reflected by POIs' business time. Specifically, during each time slot, the opening time is used to determine weights associated with each POI. The weight is calculated as the ratio of the opening hours during each time period. It ranges from zero to one: if a POI is closed during a particular time period, the weight will be zero; if it is opened during the whole time period, the weight will be one. Since multiple periods need to be considered for digital billboard advertising, we extend the classic MCLP to address the dynamic semantics of the environment. The following additional notations are included:

$j$ = index of demand points (i.e., POIs) where $j = 1, 2, \ldots J$.

$h_{jt}$ = demand for service at point $j$ (i.e., weight of a POI at $j$) during period $t$

$N_j$ = the set of the potential facilities (i.e., billboards) capable of covering demand (i.e., a POI) at $j$

$$\beta_{jt} = \begin{cases} 1, & \text{if demand (i.e., a POI) at } j \text{ is covered by at least one facility (i.e., billboard) during period } t \\ 0, & \text{otherwise} \end{cases}$$

Using the above notations, the dynamic environment model is defined as follows:

$$Maximize: \quad f_2 = \sum_{j}^{J} \sum_{t}^{T} h_{jt} \beta_{jt} \tag{10}$$

$$Subject\ to: \quad \sum_{k \in N_j} x_{kt} \geq \beta_{jt} \quad \forall j, \forall t \tag{11}$$

$$\sum_{t}^{T} \sum_{k}^{K} x_{kt} = p \tag{12}$$

$$x_{kt} \in \{0, 1\}, \quad \forall k, \forall t \tag{13}$$

$$\beta_{jt} \in \{0, 1\}, \quad \forall j, \forall t \tag{14}$$

The objective function (10) seeks the maximization of the POI coverage over the whole time horizon. Constraint (11) checks whether POI at point $j$ during period $t$ is suitably served by one or more billboards. Constraint (12) defines that the $p$ billboards are to be selected in $T$ periods. Constraints (13) and (14) specify that the decision variables are binary.

### *3.5. Integrated matching*

In order to achieve a high degree of matching with both the target audience and the environment, the dynamic audience model and the dynamic environment model are combined into a dynamic integrated model, which has two objectives. The weighted sum (Cohon and Marks 1978), min-max (Lightner and Director 1981), and the non-dominated sorting genetic algorithm (NSGA) (Srinivas and Deb 1994, Deb *et al.* 2000) are commonly used methods to solve multi-objective optimization problems. Each method has its strengths and weaknesses. The selection of a specific method often depends on the information available in the problem, the solution requirements, and other factors (Marler and Arora 2004). The weighted sum method is computationally efficient, but heavily depends on weight selection (Cao *et al.* 2012). As for outdoor advertising, the advertisers usually have a clear goal and can concretely define what they prefer. Their prior knowledge is sufficient to select a suitable weight, so the weighted sum method is applied in this study. This involves the introduction of two weighting coefficients associated with each objective, namely $g_1, g_2$. These two weights, ranging between 0 and 1, indicate the relative importance of the corresponding objective. Using the weighting method, objectives (5) and (10) can be replaced by a single-objective, objective function (15):

$$Maximize \quad g_1 f_1 + g_2 f_2 \tag{15}$$

$$g_1 + g_2 = 1 \tag{16}$$

As objectives $f_1$ and $f_2$ have different magnitudes, the normalization scheme below is adopted first to make them comparable (Mausser 2006).

$$f^s = \frac{f - f^{min}}{f^{max} - f^{min}} \tag{17}$$

where $f^s$ is the normalized objective function, $f^{min}$ and $f^{max}$ are the lowest and highest values that the objective function can achieve.

After normalization, each objective function values ranges from 0 to 1. The combined objective function becomes:

$$Maximize \quad g_1 \frac{f_1 - f_1^{min}}{f_1^{max} - f_1^{min}} + g_2 \frac{f_2 - f_2^{min}}{f_2^{max} - f_2^{min}} \tag{18}$$

## 4. Experimental results

### *4.1. Study area and dataset*

The proposed dynamic models were applied to site digital billboards in Wuxue, a county-level city on the north shore of the Yangtze River, in Hubei province, China. In total, there are 382 county-level cities in China, and more than 241 million people live in county-level cities (National Bureau of Statistics of China 2019). Contrary to approaching saturation in the outdoor ads market in first-tier and second-tier cities in China, county-level cities are experiencing rapid growth and believed to have huge outdoor ads market potential (Beyond Summmits 2019). Wuxue, as a typical representative of county-level cities, contains 12 sub-districts, with a total area of 1200 km$^2$. Among these sub-districts, the Wuxue sub-district forms the center of the city. As shown in Figure 3, the density of cell phone towers in the Wuxue sub-district is higher, and the majority of the residents live there. So in this study, this area was used as a demonstration of our model implementation.

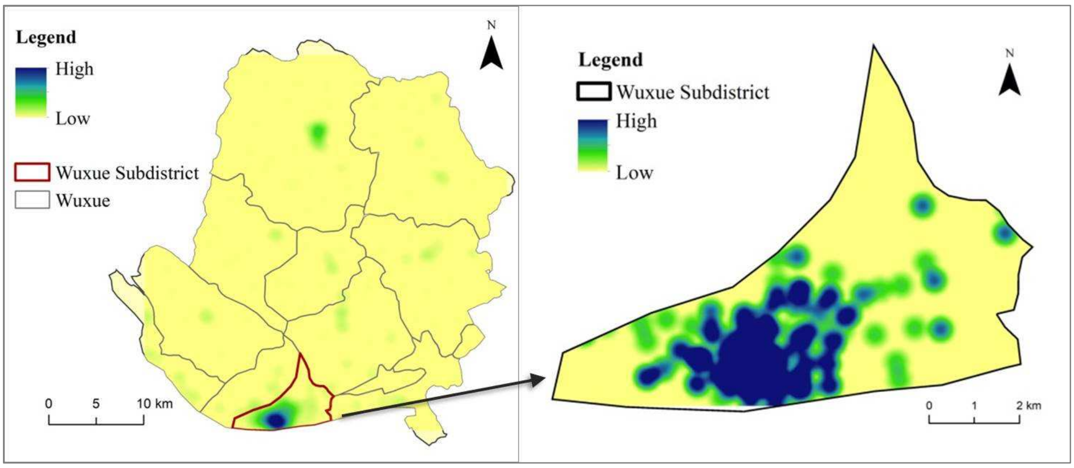


Figure 3 Location of the study area and spatial kernel density of the distribution of cell phone towers

The mobile phone dataset used in this study was provided by a major Wuxue cellular operator for research collaboration. It contains two parts, the mobile internet usage data, and mobile phone location data, from 10th of August 2015 to 29th of August 2015. Since dynamic billboard placement requires fine-grained temporal resolution data, we selected the users who had at least one location record every hour and at least one mobile internet usage record every day during the whole time span for analysis, yielding 8,507 total users.

The POI data were retrieved from Baidu Maps in August 2017[1], which is one of the most popular web mapping services in China. We obtained POI records using the Baidu Maps Application Programming Interface (API). In total, 2,212 records of Baidu POIs were obtained within the study area, belonging to 16 categories. Among them, there are 638 records of retail stores as our target POIs. Figure 4 gives the locations of all categories of POIs and retail stores in the study area. The business hours of the target POIs were acquired from DaZhong DianPing, which is the largest location review website in China.

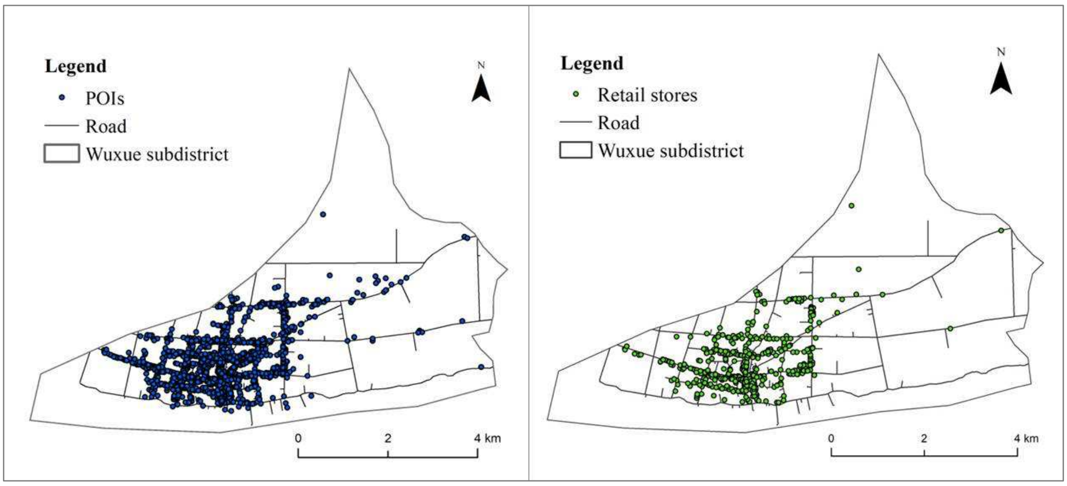


Figure 4 Location of all categories of POIs (left) and retail stores (right) in the study area

### *4.2. Spatio-temporal dynamics of target audience*

Using the method in Section 3.3, we grouped the users into different interest clusters according to their primary interests. Finally, we identified 539 users as our target audience whose primary interest was online shopping.

Media agencies may sell ad space at different temporal divisions. Some will offer hourly time slots (David 2017), while others just distinguish peak times and off-peak times (Blip 2018). The slot is the minimum time segment that can be rented by an advertiser. In this study, since we did not conduct a real advertising campaign with a media agency, we divided a weekday into six advertisement time slots by considering the typical rhythm of daily life and main activities for urban residents (Table 4).

Table 4 Advertisement slots

| ID | **Time period** | **Main activity** |
|---|---|---|
| T1 | 00:00-07:00 | Sleep time |
| T2 | 07:00-08:00 | Morning commute time |
| T3 | 08:00-12:00 | Morning work time |
| T4 | 12:00-14:00 | Lunch time |
| T5 | 14:00-18:00 | Afternoon work time |
| T6 | 18:00-24:00 | Free time |

Next, we applied the method proposed in Section 3.3 to calculate the number of target users in a certain area for each time slot. Specifically, we first split the study area into a Voronoi diagram generated by the mobile phone towers. Using the timestamp associated with each record in the mobile phone location data, mobile phone data were divided into the above six advertisement time slots. Then, for each mobile phone tower, the distinct target users were counted during each time slot. To avoid random effects, we utilized the average value of all the weekdays in the dataset for

[1] There is a mismatch between the period of the mobile phone data and the POI data. But as there was no major urban development between 2015 and 2017 in Wuxue, we expect this mismatch will not have a big impact on the results.

further analysis. Within each demand polygon (i.e., each Voronoi polygon), the audience was assumed to be uniformly distributed.

Figure 5 shows the spatial distribution of the target audience during each time period. It can be seen that spatial distribution differs over different time periods. The distribution during T1 can be regarded as a baseline distribution of the target audience since most people were probably sleeping at home during that time. During T3, T5, and T6, the target users were distributed in a more concentrated fashion and seemed to move more frequently.

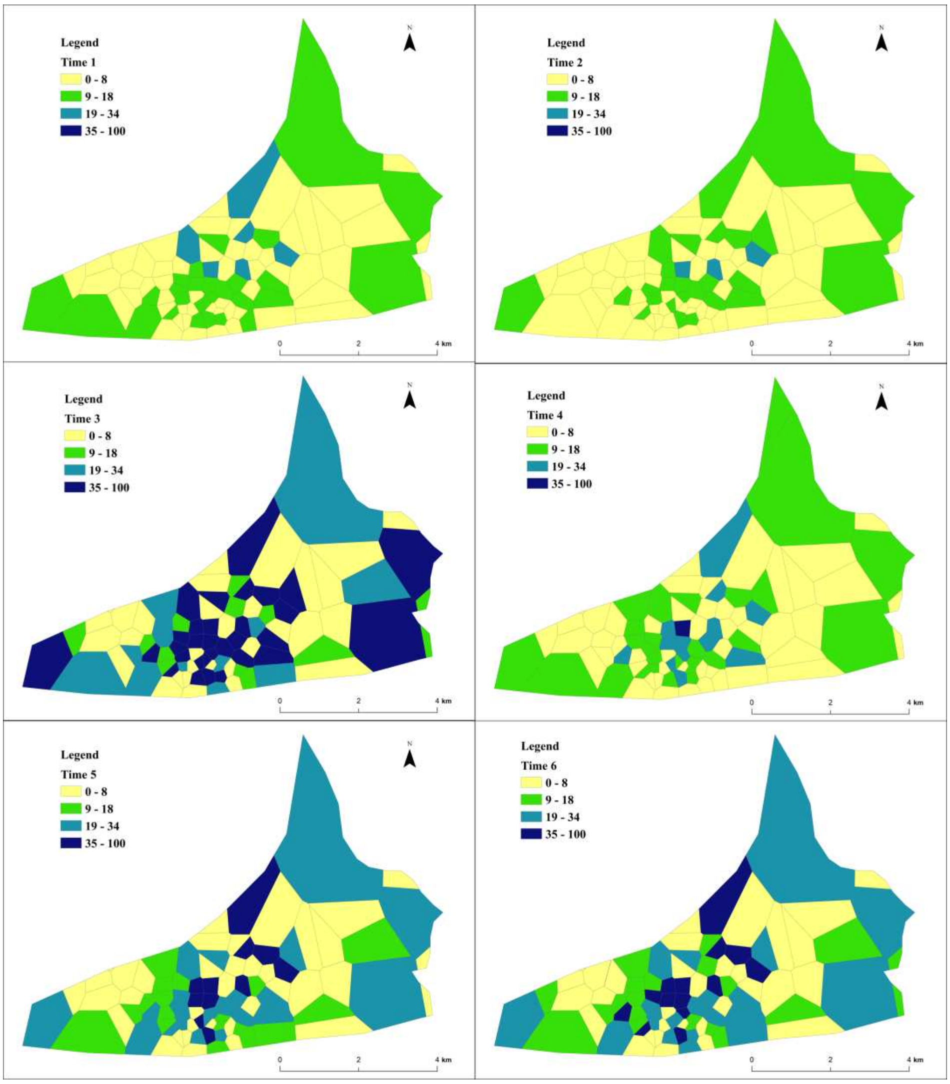

Figure 5 Spatial distribution of target audience during each time period

### *4.3. Model implementation and evaluation*

In this study, the facility used in the location models is the large-sized digital billboard. For small or medium-sized billboards, it may be inappropriate to use mobile phone data to estimate how many people near each billboard. Using a camera or Bluetooth will be more precise in that scenario. The maximum viewing distance of a billboard is usually regarded as 10 times the screen's dimension (DAKCO 2019, Euro Display 2019). The readability of a digital billboard is usually half its visibility (Euro Display 2019). So for a large billboard, e.g., 4 m by 14 m, its readability is around 250 m. Hence, a 250 m buffer around each digital billboard is used to represent its influence range. As for the candidate facility sites, the ideal way would be to use the real digital billboard locations. However, the real digital billboard data often belong to different media agencies, which makes obtaining data difficult if not impossible. As an alternative, we use the shopping POIs (Figure 4, right) as candidate places for outdoor advertising. Displaying ads in commercial areas is a commonly used strategy in the advertising industry (Inman 2016). It also corresponds with one of our objectives (i.e., environment matching).

To evaluate the effectiveness of the proposed location optimization models that consider the human mobility and the environment variation (Sections 3.3 and 3.4), respectively, we compared them with two commonly utilized models (referred to as baselines hereafter).

1) The first baseline selects the locations with the most target audiences based on their average daily flow. The temporal variation of the number of target audiences in a place is ignored. In this scenario, the MCLP-CC model was applied. This baseline is referred to as "static audience" hereafter.
2) The second baseline selects the locations where most target POIs are located. The business hours of target POIs are ignored in this case and the classic MCLP model applied. We denote this baseline as the "static environment" hereafter.

The coverages of the target audience and the target POIs over an entire day were utilized as the performance indicators to describe how effective a model is. The coverage of target audiences and POIs in each sub-period were calculated separately and accumulated to evaluate the coverage over the entire period.

In summary, five models are used in this study, namely, the three proposed models (i.e., dynamic audience, dynamic environment, and dynamic integrated model) and two baselines (i.e., static audience, and static environment). All the models were implemented in Python 2.7.2, using ArcPy for ArcGIS 10.1. The models were solved by Gurobi using the branch-and-bound approach (Morrison *et al.* 2016). This algorithm implicitly enumerates all possible solutions to the problem based on a search tree. It consists of the branching step and the bounding step. During the branching step, a node in the tree is split into several branches by dividing the possible values of a specific variable. During the bounding step, the lower and upper bounds of the objective function in a particular branch are determined. If these bounds cannot surpass the current best solution, these suboptimal branches are pruned. The tree is explored until finding the optimal solution (Garrido-Jurado *et al.* 2016, Morrison *et al.* 2016). All analysis was done on a desktop computer (Intel Xeon E3 CPU, 3.50 GHz with 16 GB RAM).

#### *4.3.1. Evaluation of audience matching*

The first experiment was to compare the target audience coverage achieved by different models. Varying the number of billboards from 6 to 42, the coverage results achieved by the dynamic audience, static audience, dynamic environment, and static environment are shown in Figure 6. For all the models, as the number of billboards increased, the target audience coverage grows correspondingly. The two audience-oriented approaches (i.e., dynamic audience and static audience) showed the superiority of reaching the target audience for all the different numbers of billboards. Dynamic audience achieved the best result, as expected. Ranging the number of billboards from 6 to 42, the proposed dynamic audience model achieved a maximum of 40 % coverage improvement compared with the baseline static audience model when $p$ was 6, while a minimum of 17 % improvement when $p$ was 42. The average coverage improvement was 27 % compared with the static audience model.

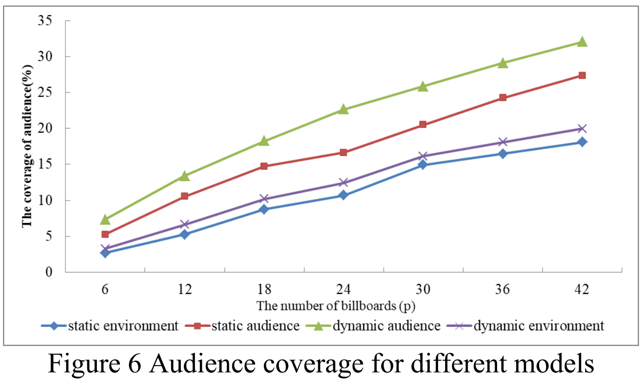

Figure 6 Audience coverage for different models

To better compare the results achieved by different methods, we visualized the development of results in 3-D. Each selected billboard place is represented by a cylinder. The cylinder is composed of 6 timeslots (T1, T2, T3, T4, T5, T6). The selected timeslot is highlighted in red color. Taking $p$ = 12 as an example, Figure 7 shows the spatio-temporal deployment of billboards calculated by the dynamic audience and the static audience model, respectively. Note that we assumed 6 ad periods per day, and for static models, the billboard places were fixed during a day. So when $p$ was 12, for static models, only two places were selected (Fig. 7, right). Concerning the dynamic audience model (Fig. 7, left), the ad display time was concentrated on T3, T5, and T6, which is consistent with Figure 5. The target audiences were spatially more concentrated during these periods. Specifically, seven billboards were selected to display during T3, followed by three during T6, and two during T5. As for the geographical locations of the selected sites, both the dynamic and the static model were concentrated in the central urban area.

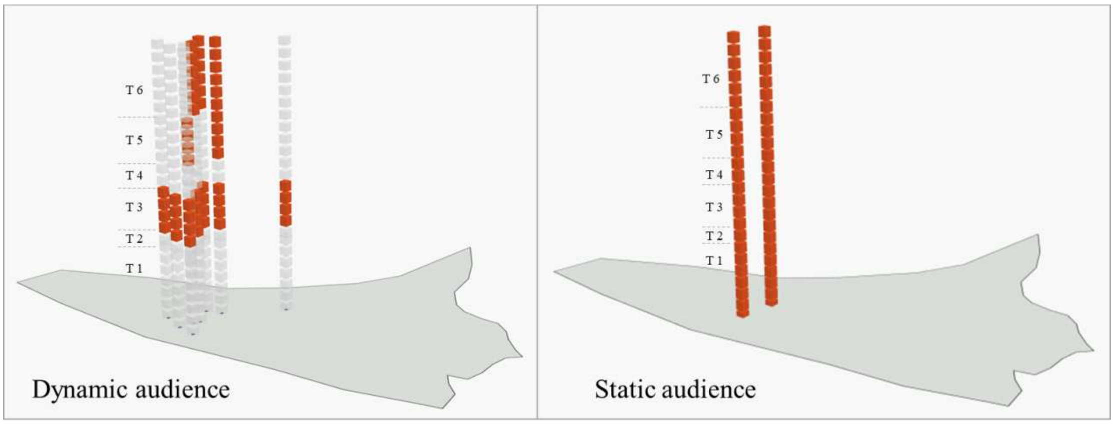


Figure 7 Audience matching: The spatio-temporal deployment of billboards with $p$ = 12. Time slots marked in red color indicates that they are selected for ads displaying.

### 4.3.2. *Evaluation of environment matching*

In the second experiment, we compared the POI coverage achieved by different models (Fig. 8). The two POI-oriented models (i.e., dynamic environment and static environment) both showed better POI coverages compared with the two audience-oriented models. The proposed dynamic environment model achieved the best coverage results, followed by the static environment. Varying the number of billboards from 6 to 42, the dynamic environment model achieved a maximum of 38 % coverage improvement compared with static environment method when $p$ was 12, while a minimum improvement of 21 % was obtained when $p$ was 42. The average coverage improvement was 29 % compared with the static environment model.

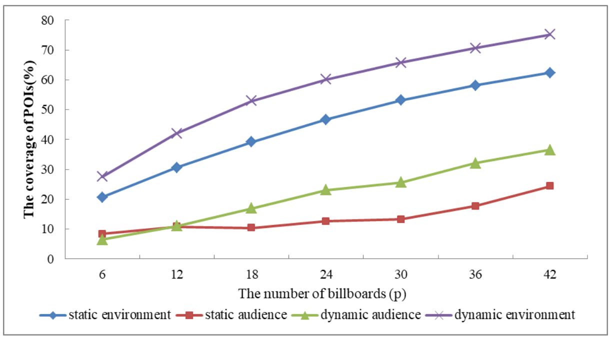


Figure 8 POIs coverage for different models

Figure 9 depicts the spatio-temporal deployments of billboards calculated by the dynamic environment and the static environment model, respectively, when $p$ was 12. The ad display time resulting from the dynamic environment model was concentrated on T3, T4, and T5, since during these periods, almost all the target POIs were opening.

To gain more insight on the proposed approach, we investigated the POIs within the influence area of the selected places. Both the static and dynamic environment models selected areas with a high density of retail stores, and they have two shared places. The representative retail store in each influence area was highlighted with the corresponding picture (Fig. 10). The dynamic environment model is more efficient in using the billboards, however, since it focused on the opening hours of the retail stores to display the ads.

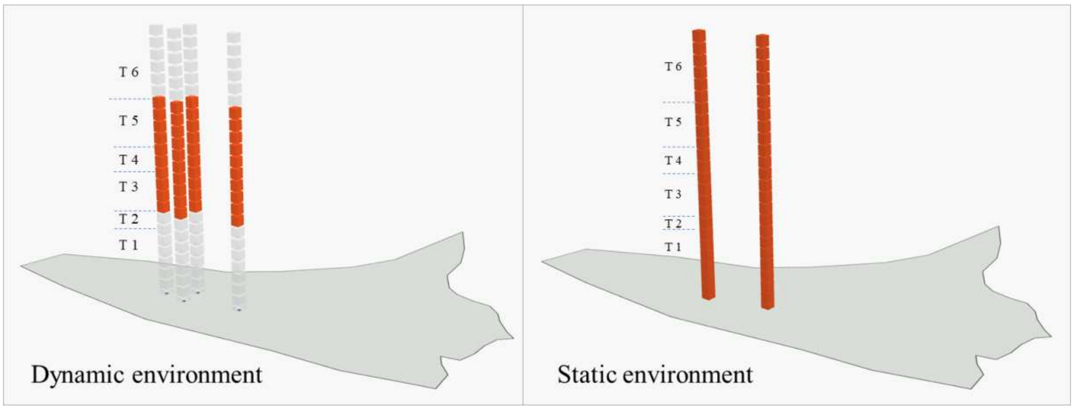

Figure 9 Environment matching: The spatio-temporal deployment of billboards with $p$ = 12. Time slots marked in red color indicates that they are selected for ads displaying.

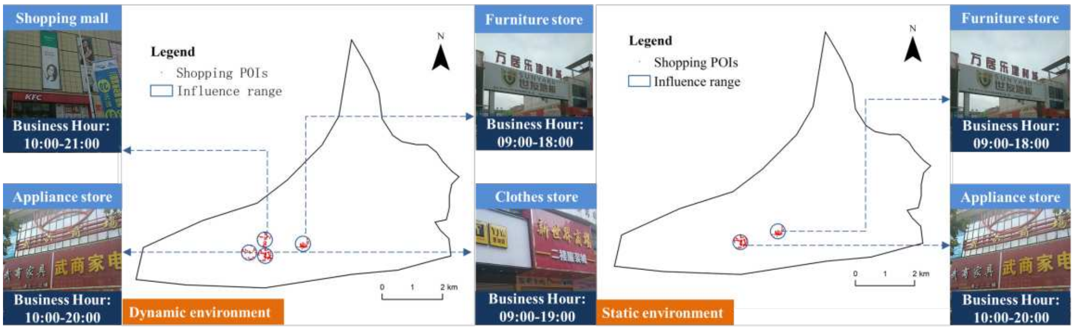

Figure 10 Representative retail stores within the influence area

### *4.3.3. Evaluation of the integrated matching*

The dynamic integrated model was employed to integrate both the audience matching degree and the environment matching degree. Here, we took $p$ =12 as an example, so the spatio-temporal deployment of billboards calculated by the integrated model can be compared with previous results (Fig. 7, Fig. 9). In order to investigate the influences of the weights, we varied $g_1$ from 0 to 1, with an increment of 0.1, and 11 solutions were obtained as shown in Table 5. Choices of weights are determined by advertisers' preference for the audience matching degree or the environment matching degree, respectively. A larger weight results in higher priority of the corresponding objective, and vice versa. In Table 5, the first and last rows provide the solutions for the scenarios when only one objective is considered, which is equivalent to solving each single-objective model that is, the dynamic audience and the dynamic environment model, respectively. Each objective function value ranged from 0 to 1 after normalization. Table 5 also shows several other solutions between these two extreme scenarios. In general, there is a trade-off between the audience matching degree and the environment matching degree when applying this integrated model. In this case, an increase in the audience matching degree is often accompanied by a reduction in the environment matching degree. A more balanced trade-off is where both the audience matching degree and the environment matching degree are given the same emphasis. In this case, when $g_1 = 0.5$, the value of objective 1 is 0.77, and the value of objective 2 is 0.86. The sum of them is the highest among other solutions in Table 5. The corresponding spatio-temporal deployment of billboards can be considered as the best solution when both the target audience matching degree and environment matching degree are considered (Fig. 11). The most selected time period was T3, since during this time period, most target POIs were opening and the target users were spatially concentrated. During T4, different from four billboards selected by the dynamic environment model (Fig. 9), only one billboard was selected by the integrated model. During T5, four billboards were selected. This is how this integrated model balances the two competing goals.

Table 5 Dynamic integrated model results ($p$=12)

| $g_1$ | $g_2$ | Objective 1 Target audience | Objective2 Target POI | Overall performance |
|---|---|---|---|---|
| 1 | 0 | 1 | - | |
| 0.9 | 0.1 | 0.99 | 0.32 | 1.31 |
| 0.8 | 0.2 | 0.98 | 0.43 | 1.41 |
| 0.7 | 0.3 | 0.89 | 0.70 | 1.59 |
| 0.6 | 0.4 | 0.87 | 0.73 | 1.61 |
| 0.5 | 0.5 | 0.77 | 0.86 | 1.63 |
| 0.4 | 0.6 | 0.65 | 0.95 | 1.60 |
| 0.3 | 0.7 | 0.58 | 0.99 | 1.57 |
| 0.2 | 0.8 | 0.58 | 0.99 | 1.57 |
| 0.1 | 0.9 | 0.55 | 0.99 | 1.54 |
| 0 | 1 | - | 1 | |

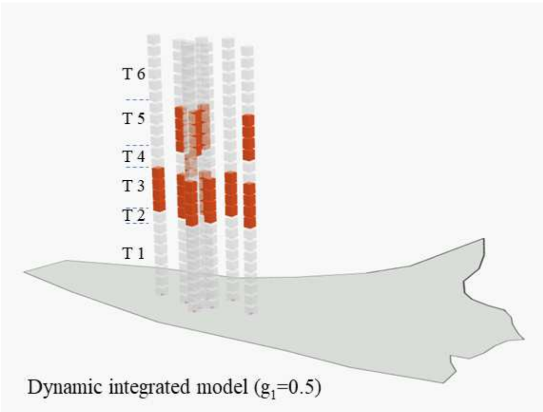


Figure 11 Spatio-temporal deployment of billboards in the dynamic integrated model. Time slots marked in red color indicates that they are selected for ads displaying.

## 5. Discussion

In order to assess the robustness of the proposed models, a sensitivity analysis was performed by varying the buffer radius from 50 m to 500 m. The number of billboards is set to 12 ($p$ = 12). For each buffer size, the audience coverage results (Figure 12) and the POI coverage results (Figure 13) achieved by the four models are compared. It can be observed that with the increase of the buffer, the performance of all models becomes better, because a single billboard can cover more target audiences, and POIs. The dynamic audience model showed the superiority of reaching the target audience for all the different buffer sizes. Similarly, the proposed dynamic environment model achieved the best coverage results for all the different buffer sizes. It demonstrates that our models can achieve better results under different scenarios[2].

[2] As the road network might also be a potential factor that affects the viewing distance of billboards, we implemented a further experiment using service areas with road network distances. The results are presented in the Appendix, and again showed the superiority of the proposed dynamic audience model and dynamic environment model, compared to state-of-the-art static models.

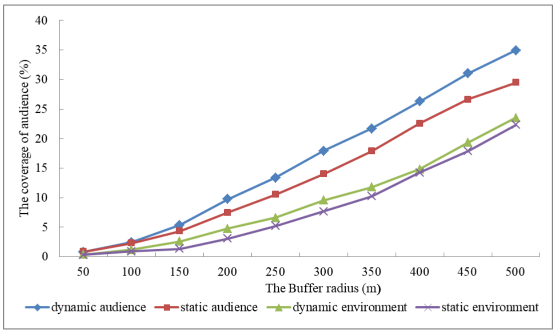

Figure 12 Effect of varying the buffer radius on the coverage of audience ($p$=12).

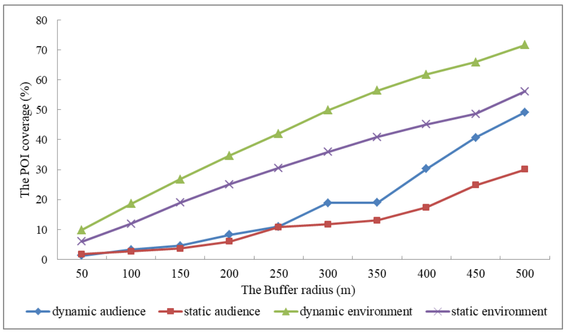

Figure 13 Effect of varying the buffer radius on the POI coverage ($p$=12)

In this study, we observe different target audience distributions during different timeslots and incorporate this temporal variability into location models. In contrast, in many of the existing location models, population-based demand is often estimated based on where people live, primarily using the static residential information. This can be defective as people may not always start their trips from home (Tong *et al.* 2019). Nowadays, big geospatial data like mobile phone location data provide finer spatial and temporal resolutions to study human mobility. In this study, we make use of these data to model the spatio-temporal dynmaics of human mobility, and incorporate them into the location models. The evaluation results show that considering these spatio-temporal dynmaics of users' trave behavior helps to provide better audience coverage and environment matching, and thus potentially improves the effectiveness of the ads displaying. While we focus on optimizing ads displaying, the proposed models can also be used for other facility siting, e.g., bicycle sharing stations, or safety cameras.

There are also some limitations of this work. Firstly, due to the limited data, the evaluation of the environment is currently solely based on the target POIs. More features should be considered in the future when enough data are available. For example, the density of the existing billboards could be included, because the audience's attention would be distracted and the effectiveness of advertisements would be deteriorated, when they are exposed to a high number of co-occurring ads. Besides, currently, the temporal variation of the environment is only reflected by POIs' business time. Social media data is a potentially powerful source to estimate the popularity of POIs with time (McKenzie, Janowicz, Gao, and Gong 2015, McKenzie, Janowicz, Gao, Yang, *et al.* 2015). It can further be incorporated to provide more insight into the temporal variation of the environment. Secondly, this work does not consider the computational load of the models. When the number of billboards increases, the computational load of the models will increase. More efficient solution algorithms, such as the greedy heuristic algorithm and simulated annealing (SA), should be employed to solve the models. Thirdly, we assumed that the influence range of all the billboards is the same. In future studies, a model that takes into account the existence of different sizes of billboards (with different radius of coverage) could be established, leading to more realistic meaning. Meanwhile, the evaluation of the proposed models with the baselines can be also improved, e.g., by counting the number of actual covered users after the placement of the ads on corresponding billboards. For this purpose, mobile phone location data and internet usage data might be applied again.

## 6. Conclusion and future work

In this study, we demonstrated how the new dataset, i.e., mobile phone internet usage data, mobile phone location data, and POI data can be combined with location models to provide an optimal deployment plan of billboards over both the spatial and temporal dimensions. Three optimization models considering various advertising needs are proposed: a dynamic audience model to maximize the coverage of the target audience, a dynamic environment model to maximize the coverage of target environment, and a dynamic integrated model to jointly maximize the coverage of both the target audience and environment. Our experimental results showed that considering the spatio-temporal variability of the target audience and the environment allows to better reach the right users and right environments, and therefore helps to display outdoor advertisement at the right time and place. We trust that this work can help advertising planners make more informed decisions and make better use of billboard resources.

Mobile phone data usage often raises privacy concerns. To address this concern, direct personal identifiers were removed, and each user was given an anonymous ID in this study. Besides, our algorithms processed location records aggregated at the group (target audiences) level, making it difficult to drill down to anyone's individual data. More sophisticated techniques for further increasing the level of privacy protection are also available now (Huang, Cheng, *et al*. 2019). Good data protection practices and ethics are also essential in research involving mobile phone data. During data processing, researchers should comply with the specific rules and local data protection laws. Researchers are responsible for storing research data securely at all times and always remove direct personal identifiers. After research, researchers should also use fully anonymized extracts when sharing research outputs.

As future work, we are interested in exploring the use of social media data to improve the modelling of the spatio-temporal dynamics of users' travel behaviors and environments, and incorporate these insights into the proposed models to improve the effectiveness of the ads displaying. We will also consider the varying influence ranges of different billboards. Meanwhile, this study mainly focused on the optimization of one advertising campaign. We intend to further extend it toward optimizing from the perspective of the entire network, where multiple categories of ads need to be distributed. Moreover, we are also interested in applying the proposed models for other applications, e.g., for optimizing the placements of bicycle sharing stations.

### Data and codes availability statement

The data and codes that support the findings of this study are available in figshare.com with the link (https://figshare.com/s/e3ddb8206f6c12cd319c). The related mobile phone data was provided by China Mobile, and cannot be made publicly available due to the protection of participant privacy.

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